XLI CILAMCE
XLI Ibero-Latin American Congress on Computational Methods in Engineering
16-19 November, 2020 FOZ DO IGUAÇU PARANÁ - BRAZIL

Use of computational vision to estimate the weight of steel slab places on the rolling mill reheating table

Josceley C. da Silva[1], Leonardo A. Scardua[2], Gustavo M. de Almeida[2]

[1] *Graduate student*
Vitoria, 29090-585, ES, Brazil
josceley@gmail.com
[2]*Dept. Control and Engineering Automation, Federal Institute of Espirito Santo*
Serra, 29173-087, ES, Brazil
lascardua@ifes.edu.br, *gmaia@ifes.edu.br*

Abstract. The fuel consumption of the slab rolling reheating furnace is one of the largest expenses of the hot rolling mill production process. Decreasing the time between slab leakage and creation is the scenario to be achieved. It is then desired to ensure conditions for the slabs to be hung increasingly hot by eliminating a "toll" in this process, which is the weighing of the slab at the oven inlet. In a continuous hot hanging process, weighing may cause a loss of 150 ° in the temperature of the slabs. The purpose of this paper is to present a new proposal for the detection of steel slab dimensions in the hanging table using computational vision and convolutional neural networks. To achieve this goal, the Convolutional Neural Networks regression technique will be used. The regressive technique is able to identify a numerical value from a set of information, in the case of images. Networks recognized in this application will be used, such as: VGG16, DenseNet, InceptionV3, etc., in addition to networks built and trained for this process, with existing datasets and generated in this production process. At the end of the work, we want to have an intelligent system capable of detecting the width, length and thickness of the slabs in order to obtain the weight of the material, eliminating the need for other forms of dimensional measurements.

Keywords: Neural networks, Volume detection

1 Introduction

The demands of the market combined with increased competition have made the production cycle one of its premises to reduce costs and activities that are financially, socially and environmentally sustainable. In order to be competitive, companies have invested in permanent assets, seeking to increase their production volume (SHINODA,2008).

Regardless of the size of the company, the market expects that not only financial results will be generated, but also improvements are made to the processes, services or products. Such improvements, in turn, should always add value to the results. The steelmaking industry is fully inserted in this context, seeking for optimized processes, with productivity gains, lower use of resources and generation of disposable materials in the process. Real-time object detection and measurement systems are very vital tasks in the industrial process[13].

In the hot rolling process, where steel coils are manufactured from slabs, the cost of reheating the slabs accounts for approximately 40% of the total rolling cost [2]. Techniques in which the slab is hung soon after the casting process are used to reduce such cost. These techniques aim at forming slabs between 300º and 450º instead of slabs at room temperature. The target temperature is around 700º. For the success of this technique, the synchronism between the stages of the steelmaking process is paramount, since the rolling mill is increasingly fed directly by the casting process.

Bearing in mind this synchrony is necessary, the controls need to be more optimized to provide agility and safety. The identification of the weight of a slab (the largest variable to calculate the hanging time) automatically, safely and without delaying the production line is a differential in this scenario. This weighing process is performed at the furnace entrance as an additional validation of the existing information, avoiding a different hanging time than expected for a certain material. In the occasion of accelerated production, this weighing may delay the furnace slab hanging process, causing a loss of up to 150º in temperature.

The proposal is to solve this problem by applying convolutional neural network to, through the images of the slabs on the mat, identify their weight with enough precision to ensure the replacement of the mechanical weighing equipment. The paper will present how to obtain the data for analysis, comparison between the built network and existing networks used in this work and the conclusion about the viability of this solution.

2 Data and Method

The objective of this work is to identify an artificial neural network architecture that is trained to obtain the dimensions of the steel slabs on the hanging table of a steelmaking company located in the state of Espirito Santo, Brazil. In this process, pre-trained networks will be analyzed. Training simulations and parameter changes will be performed in order to identify which network best fits the purpose of the paper and if, once this network is found, it would allow a sufficient level of reliability to replace the mechanical weighing.

2.1 Data Collection

There is a process for acquiring images of the slabs at the rolling furnace entrance. These images (9 per slabs) are obtained for identification through the OCR of the slabs code. This information is used to ensure that the slab planned to be rolled is actually the slab that is physically being hung. Below is the image of the conveyor belt that takes the slabs to the furnace entrance, where the camera can be found highlighted. The furnace is the equipment on the left of the figure 1. In figure 2 there is a front image of the slab.

Figure 1. Entrance of the Rolling Furnace

Figure 2. Image of the slab

In order to execute this work, images of the hung slabs were obtained between August 13 2019 until August 22 2019, making up a total of 49,734 files. The images were individually analyzed and those that made it unable to identify the dimensions were discarded. By extracting a single image per slab, there were, at the end, 4,956 files to be processed in this work. As it can be seen, the current position of the camera does not allow the accurate visualization of the length. This situation is the same for virtually all the images (except for the short slabs). In this sense, obtaining weight information is made difficult as it will be demonstrated later on. In addition to the images, the data on the dimensions of these slabs were also obtained. These data are measured in the inspection after the production of the material. There are 4 dimensions in this data file: thickness, width, length and weight. The table 1 shows some examples of the dimensions obtained.

Table 1. Slab Information

Slab ID	Thickness (mm)	Width (mm)	Length (mm)	Weight(kg)
1353956011	225	1462	9000	22870
1357415561	225	1855	6520	21240
1369234061	225	1266	11453	25490
1360712031	250	1820	7210	25430
1360712061	250	1820	5110	18040

Due to the manufacturing process, there are only 3 thickness measures: 200, 225 and 250. Therefore, the analysis of the calculation of that dimension should not be completely covered in this paper. Given that, the focus of this paper is on the dimension that provides reliable information: the width.

2.2 Neural Networks

The Artificial Neural Networks (ANNs) are computational models, composed of simple processing elements, called artificial neurons, that apply a certain mathematical function to the data (activation function), generating a single response. These neurons are connected to each other through connections, and these connections are usually associated to coefficients called weights, which are adjusted by training/learning, being responsible for the removal of the peculiarities from the database and the storage of the knowledge of the networks. (BRAGA et al., 2007).

According to Binoti et al. (2010), an artificial neuron is the information processing unit of an ANN, consisting of "n" entries x1, x2,. xn (dendrites) and one y output (axon). The inputs are associated with weights w1, w2,..., wn representing the synapses, which can be negative or positive. Currently, a basic artificial neuron model can be mathematically represented as:

$$Y_k = \varphi(V_k)$$

where: Y_k = output of the artificial neuron; φ = activation function; V_k = result of the linear combiner, that is:

$$V_k = \sum_0^m x_m . w_m$$

where: Vk = linear combiner; xm is the number of inputs; and wm is the weight for each input of m.

For the adjustment of ANNs, the numerical variables were linearly normalized in the 0 to 1 range. The input layer was composed of two neurons, being one neuron for each predictive numerical variable, according to the response/output variable. As output, the total volume per plot was used. The networks were composed of only one hidden layer, in which the number of neurons in this layer was equal to two (which corresponds to the number of neurons in the input layer), so the architecture of the network was 2-2-1, and as the activation function the sigmoid one was used.

The sigmoid activation function is the most used function in the elaboration of artificial neural networks (HAYKIN, 2001), and it is mathematically represented as:

$$\varphi(v) = \frac{1}{1+exp^{\beta u}}$$

where: φ = sigmoid activation function; β = estimate of the parameter that determines the inclination of the sigmoid function; u = potential of function activation.

It is advised that when using ANNs, simpler configurations are suggested, with as few neurons as possible in the hidden layer, so as to avoid overfitting. This consists in the exaggerated learning of the information contained in the data offered to the networks, since they become so well trained on the data set that they end up copying not only the structural similarity between the variables, but also the noise (relationship error). Consequently, these overfitting networks cannot be used in the data set as a whole, since their generalization capacity has been compromised. Simpler configurations also facilitate the process of search and configuration optimization for a given task (RUSSEL and NORVIG, 2010).

The option to choose the training algorithm interferes, specifically, in the escape of local minimums, in the performance of the desired task and in the duration of training. In the present study, the training algorithm utilized was the resilient propagation, proposed by Riedmiller and Braun (1993), as the most efficient and recommended alternative for ANNs of the Multilayer Perceptron type.

According to Carvalho et al. (1998), a well-defined set of rules to solve a learning problem is called a training algorithm. In resilient propagation the weights are based on information from the current data. For that, the individual value of updating is introduced for each weight. Initially the weights of all networks were randomly generated (HEATON, 2010). Subsequently, this individual update value evolves during the learning process based on the error function. The volume estimates were simulated with the possible combinations of the input variables, totaling three combinations for the response variable.

It should be noted that the learning of the networks was of the supervised type, therefore, two sets of values were given to the networks: the set of input values and the set of output values. Thus, the training consists of a problem of optimizing network parameters (their synaptic weights) so they can respond to inputs as expected, until the error between the output patterns generated by the network reaches the desired minimum value (PORTUGAL, 1995). The issues treatable through neural networks can be divided into three main types: function approximation, pattern classifier, and data clustering.

The Convolutional Neural Networks (CNN) is a type of neural network commonly used for image classification. It is usually divided into two parts: obtaining characteristics and the traditional network. The extraction is performed through layers of filters and actions on the images, teaching the network to identify the characteristics of the images. The figure 3 is an example of an CNN for character identification.

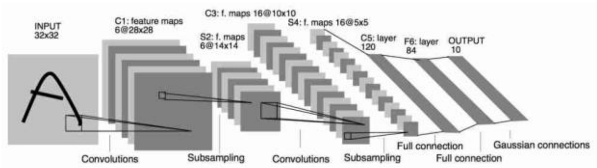

Figure 3. An Convolutional Neural Network

3 Results

For the issue proposed in this paper, an CNN used for property pricing [6] was used as the basis. The structure of this network is of function approximation (regressive). For the training the Anaconda software with Python language was chosen along with TensorFlow, Keras API libraries and others. In this paper we will name this network as Slab Dimensional Network - SDN. A built SDN structure is shown in figure 4.

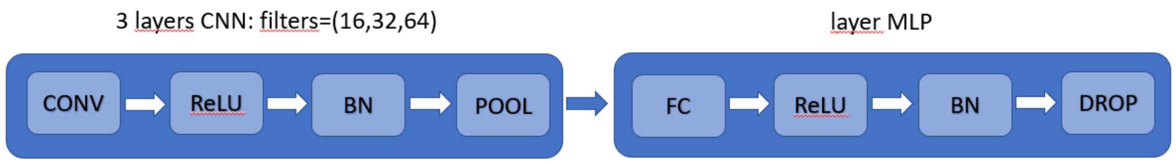

Figure 4. An CNN network model

During the SDN construction phase, several architectural changes were tested such as: more CNN layers, filter changes, MLP layer changes, etc.

The following networks are made available on Keras and were trained with the DataSet of this paper having the purpose to be compared to the SDN network: Densenet, VGG16, VGG19, InceptionV3, Xception e MobileNetV2. The work was then carried out with the dimensions of width and weight. In the case of the SDN, images were trained with a 64, 128 and 256 shape. The pre-existing networks had a single dimension trained. For all networks, the execution was to randomly use 100 images. This process was executed 5 times. The figure 5 below shows the result of one of these executions. For the first slab below the difference between the measured width (official) and the calculated width was of 49.89mm, which corresponds to an error of 3.80%.

```
Nome: raw20190821144748-9.jpg - largura Medido(a): [1310] - largura Calculado(a): [1260.1093] - Diferença [49.890747] - % [3.808454]
Nome: raw20190816184450-9.jpg - largura Medido(a): [1314] - largura Calculado(a): [1260.1093] - Diferença [53.890747] - % [4.1012745]
Nome: raw20190815164856-9.jpg - largura Medido(a): [1253] - largura Calculado(a): [1260.1093] - Diferença [7.109253] - % [0.5673785]
Nome: raw20190813232321-9.jpg - largura Medido(a): [1266] - largura Calculado(a): [1260.1093] - Diferença [5.890747] - % [0.46530387]
Nome: raw20190822172020-9.jpg - largura Medido(a): [1245] - largura Calculado(a): [1260.1093] - Diferença [15.109253] - % [1.2135946]
Nome: raw20190815120026-9.jpg - largura Medido(a): [1866] - largura Calculado(a): [1612.4392] - Diferença [253.56079] - % [13.588467]
Nome: raw20190813133304-9.jpg - largura Medido(a): [1460] - largura Calculado(a): [1514.227] - Diferença [54.22705] - % [3.7141817]
Nome: raw20190818192129-9.jpg - largura Medido(a): [1258] - largura Calculado(a): [1260.1093] - Diferença [2.109253] - % [0.16766717]
Nome: raw20190814061530-9.jpg - largura Medido(a): [1266] - largura Calculado(a): [1260.1093] - Diferença [5.890747] - % [0.46530387]
Nome: raw20190814200510-9.jpg - largura Medido(a): [1258] - largura Calculado(a): [1260.1093] - Diferença [2.109253] - % [0.16766717]
Nome: raw20190815011148-9.jpg - largura Medido(a): [1255] - largura Calculado(a): [1258.184] - Diferença [3.18396] - % [0.25370198]
Nome: raw20190821004055-9.jpg - largura Medido(a): [1250] - largura Calculado(a): [1260.1093] - Diferença [10.109253] - % [0.80874026]
Nome: raw20190814224046-9.jpg - largura Medido(a): [1152] - largura Calculado(a): [1202.1143] - Diferença [50.114258] - % [4.350196]
Nome: raw20190818015334-9.jpg - largura Medido(a): [1254] - largura Calculado(a): [1260.1093] - Diferença [6.109253] - % [0.48718125]
```

Figure 5. Details of the execution result

The SDN result can be found on table 2 with each of the SHAPE results. The Val Loss was obtained during the network training and the mean values are based on the 5 processing mentioned.

Table 2. SDN execution result

Network	Dimension	Shape	Val Loss	Mean Dif.(mm)	Mean Dif.(%)
		64	1.94	30.69	2.23
SDN	Width	128	2.01	32.87	2.58
		256	1.88	32.52	2.31
		64	8.56	1687.22	6.76
SDN	Weight	128	7.99	2191.32	10.46

As it can be seen, the variation in image shape is irrelevant for the final result. The inclusive difference is with the smaller shape: 64. The comparison between weight and width is really considerable, and the difference percentage being up to 3 times larger. This is explained by the lack of images that can clearly display the 3 dimensions of the slab.

The table 3 shows the result of the width and weight dimensions for the pre-trained networks.

Table 3. Execution result of the pre-trained networks

Network	Dimension	Val Loss	Mean Dif. (mm)	Mean Dif. (%)
Densenet	Width	2.47	58.28	4.25
	Weight	9.44	2794.84	12.16
VGG16	Width	2.43	43.78	3.17
	Weight	21.01	4522.02	23.00
VGG19	Width	6.68	96.76	6.87
	Weight	9.15	3840.57	22.54
InceptionV3	Width	6.68	97.66	7.13
	Weight	9.40	3268.10	14.58
Xception	Width	6.68	92.68	6.72
	Weight	8.11	3975.82	18.29
MobileNetV2	Width	2.28	73.34	5.48
	Weight	8.43	4292.20	22.73

Similar to the SDN network, the result for weight evaluation shows a fairly noticeable divergence from the expected. The width calculation, in turn, shows the VGG16 network and Densenet with results close to the SDN. It is important to highlight that the weights of these networks were not made for this type of image, they are networks of satisfactory characteristics. Without images that allow the evaluation of the three dimensions of the slabs, the work was focused on the assertiveness of one of the dimensions: the width.

When evaluating the widths of the slabs on DataSet, 56% of the slabs have between 1201 and 1300mm. The figure 6 shows that in this dimension interval, the mean values of the differences, as well as the percentage, is much smaller in this range, as expected.

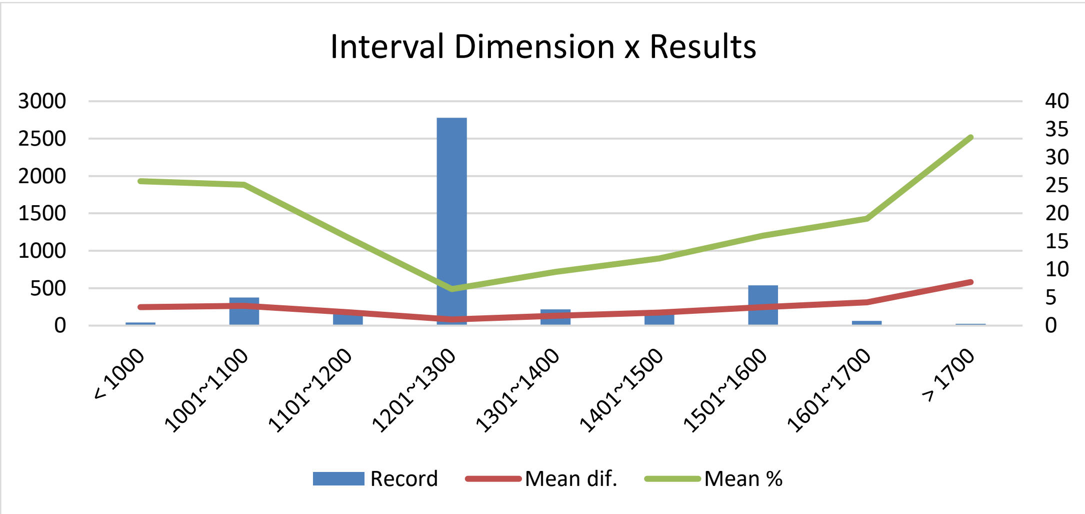

Figure 6. Interval Dimension x Results

As it is shown in Figure 6, the assertiveness of the width value can be obtained by increasing the dataset in widths that do not envision the most common range (width smaller than 1200 and larger than 1300). By increasing the dataset in these ranges, an assertiveness close to the range of 1200 to 1300 can be obtained.

4 Conclusions

For the application in the industry, a difference of up to 5% of the calculated weight is acceptable[2]. Considering the SDN result of 6.76%, it shows that managing to obtain a dataset with images of three dimensions of the slabs, the network can be trained to respond in accordance with the weight of the material, which is the objective of this paper.

The pre-existing networks, in comparison to the SDN, had a lower result and were deemed not adequate for the matter of this paper. The reason is that they were trained with images very different from the images proposed in this paper. The SDN had a low average difference result (2.6%), which proves that it is possible to make the option to identify the width an actual option for the industry.

This paper aimed to present, without exhausting the subject, a solution capable of satisfactorily solving the problem of weight calculation through computer vision of steel slabs. The results obtained indicate this solution as fully capable of being applied in an industrial environment in an experimental way, considerably increasing productivity and guaranteeing the quality of manufactured products. However, if used without proper assessment and care, it may result in inaccurate measurements.

References

[1] C. Shinoda, "Viabilidade de projetos de investimento em equipamentos com tecnologia avançada de manufatura". Publisher, 2008
[2] A. TUBARÃO. "Sumário A ArcelorMittal Tubarão no Espírito Santo". *Publish*. http://tubarao.arcelormittal.com/pdf/galeria-midia/relatorios-publicacoes/sumarioarcelormittal-tubarao-es.pdf, 2017.
[3] A. P. Braga and A. P. Carvalho and T. B. Ludemir. "Fundamentos de redes neurais artificiais." *Rio de Janeiro: DCC/I, COPPE/ Sistemas*, NCE/UFRJ, 1998. 246p.
[4] Z. L. Kovacs. "Redes neurais artificiais: fundamentos e aplicações". *2.ed. São Paulo: Colledium Cognitio*, 1996. 174p.
[5] S. Haykin. "Redes neurais: princípios e prática". 2.ed. Porto Alegre: Bookman, 2001. 900p.
[6] A. Rosebrok. "Keras, Regression, and CNNs" https://www.pyimagesearch.com/2019/01/28/keras-regression-and-cnns, 2019.
[7] S. Russel and P. Norvig. "Artificial Intelligence: A Modern Approach". *3 ed. Editora Pearson, 2010*, 1.152p.
[8] F. A. Leal and E. P. Miguel. "Redes Neurais Artificiais na Estimativa de Volume em um Plantio de Eucalipto em Função de Fotografias Hemisféricas e Número de Árvores". *Publish*
[9] M. Riedmiller and H. Braun. "A direct adaptive method for faster back propagation learning: the rporp algorithm". *IEEE International Conference on Neural Networks*, v.1, p.586-591, 1993.
[10] M. L. M. S. Binoti and H. G. Leite. "Aplicação de redes neurais artificiais para estimação da altura de povoamentos equiâneos de eucalipto". *Revista Árvore*, Viçosa-MG, v.37, n.4, p.639-645, 2013a.
[11] J. Heaton, "Programming Neural Networks with Encog3 in Java". *2ed. Heaton Research*, Incorporated, 2010. 240p.
[12] M. S. Portugal. "Neural networks versus time series methods: a for ecasting exercise." *Revista Brasileira de Economia*, v. 49, n. 4, p. 611-629, 1995.
[13] N. A. Othman and M. U. Salur and M. Karakose and I. Aydin. "An Embedded Real-Time Object Detection and Measurement of its Size." *2018 International Conference on Artificial Intelligence and Data Processing (IDAP)*, 2018.